Optimization notes

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Directional derivative

From a starting point $\underline{x}_0$ and a given dirction $\underline{u}$:

- $\underline{x}(\lambda) = \underline{x}_0 + \lambda \underline{u}$
  - λ is a scalar.
- $d\underline{x} = \underline{u} d\lambda$
  - For a small change in λ.
- $F(\lambda) = f(\underline{x}_0 + \lambda \underline{u})$

$$\begin{aligned} dF = df &= (\nabla f(\underline{x}))^\top d\underline{x} \\ &= (\nabla f(\underline{x}))^\top \underline{u} d\lambda = \nabla^\top f \underline{u} \lambda \end{aligned}$$

- $\frac{df}{d\lambda} = \nabla^\top f \underline{u}$
  - If f is minimized at $\underline{x}^* = \underline{x}_0 + \lambda \underline{u}$, then:
    - $\nabla f(\underline{x}^*))^\top f \underline{u} = 0$
    - gradient f evaluated at the minimum point is orthogonalto $\underline{u}$.

Weierstrass Theorem

If $f(\underline{x})$ is continuous on a nonempty feasible set that is cloased and bounded, then $f(\underline{x})$ has a global minimum in this set.

- A set S is bounded if for any point $\underline{x}$ in S, we have $\underline{x}^\top \underline{x} < c$
  - c is a finite positive number.

Single-variable unconstrained optimization

- Necessary condition
  - If a function $f(x)$ has a local minimum at $x = x^*$, and $f'(x)$ exists as a finite number at $x = x^*$, then $f'(x^*) = 0$.
  - x^* at $f'(x^*) = 0$ is called stationary point.
- Sufficient condition
  - Suppose $f'(x^*) = f''(x^*) = \cdots = f^{(m-1)}(x^*) = 0$, but $f^{(m)}(x^*) \neq 0$, then $f(x^*)$ is:
    - 1. a local minimum if $f^{(m-1)}(x^*) > 0$ and m is even.
    - 2. a local maximum if $f^{(m-1)}(x^*) < 0$ and m is even.
    - 3. neither a maximum nor a minimum if m is odd.

Multi-variable unconstrained optimization (1)

Definition of r^{th} differential of function f:

$$d^r f(\underline{x}^*) = \sum_{i=1}^{n} \sum_{j=1}^{n} \cdots \sum_{k=1}^{n} h_i h_j \ldots h_k \frac{\partial^r f(\underline{x}^*)}{\partial x_i \partial x_j \ldots \partial x_k}$$

Example

When (order) $r = 2$ and (number of variables) $n = 3$, we have:

$$\begin{aligned} d^2 f(\underline{x}^*) = d^2 f(x_1^*, x_2^*, x_3^*) &= \sum_{i=1}^{3} \sum_{j=1}^{3} h_i h_j \frac{\partial^2 f(\underline{x}^*)}{\partial x_i \partial x_j} \\ &= h_1^2 \frac{\partial^2 f(\underline{x}^*)}{\partial x_1^2} + h_2^2 \frac{\partial^2 f(\underline{x}^*)}{\partial x_2^2} + h_3^2 \frac{\partial^2 f(\underline{x}^*)}{\partial x_3^2} \\ &+ 2h_1 h_2 \frac{\partial^2 f(\underline{x}^*)}{\partial x_1 \partial x_2} + 2h_2 h_3 \frac{\partial^2 f(\underline{x}^*)}{\partial x_2 \partial x_3} + 2h_1 h_3 \frac{\partial^2 f(\underline{x}^*)}{\partial x_1 \partial x_3} \end{aligned}$$

Multi-variable unconstrained optimization (2)

- Necessary condition

$$\frac{\partial f(\underline{x}^*)}{\partial x_1} = \frac{\partial f(\underline{x}^*)}{\partial x_2} = \cdots = \frac{\partial f(\underline{x}^*)}{\partial x_n} = 0$$

  - In vector form, $\nabla f(\underline{x}^* = 0)$.
  - $\underline{x}^*$ at $\nabla f(\underline{x}^* = 0)$ is called stationary point.
- Sufficient condition
  - For a stationary point at $\underline{x} = \underline{x}^*$:
    - if the Hessian matrix of $f(\underline{x})$ evaluated at $\underline{x} = \underline{x}^*$ is positive definite, then $\underline{x}^*$ is a local minimum.
    - if the Hessian matrix of $f(\underline{x})$ evaluated at $\underline{x} = \underline{x}^*$ is negative definite, then $\underline{x}^*$ is a local maximum.

Hessian Matrix

- $(H_f)_{i,j} = \frac{\partial^2 f}{\partial x_i \partial x_n}$
- In matrix form: $H_f = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2 \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \frac{\partial^2 f}{\partial x_n \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}$

Definiteness

- A matrix is positive definite if all its eigenvalues are positive.
  - If some of the eigenvalues are positive and some are zero, then the matrix is positive semidefinite.
- Checking the sign of the determinants is an alternative way to determine the definiteness of a matrix.
- A twice differentiable function is convex if and only if its Hessian matrix is positive semi-definite.
  - The function is strictly convex if the Hessian matrix is positive definite.

Multivariable optimization with equality constraints

Lagrange Multiplier Theorem

- Suppose the point $\underline{x}^*$ minimizes $f(\underline{x})$ and satisfies the equality constraints: $h_j(\underline{x}^*) = 0$, for $j = 1, 2, \ldots, m$
- Assume that the constraint gradients $\nabla h_j(\underline{x}^*)$ are linealy independent.
- Then there exists a unique set λ_j^* $(j = 1, 2, \ldots, m)$ satisfying:

$$\frac{\partial L}{\partial x_i} = \frac{\partial f}{\partial x_i} + \sum_{j=1}^{m} \lambda_j^* \frac{\partial h_j}{\partial x_i} = 0$$

where $i = 1, 2, \ldots, n$.